Further on
PRES 2018
Proceedings of the 21st Conference on Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction
Guest Editors: Timothy G. Walmsley, Petar S. Varbanov, Rongxin Su, Jiří J. Klemeš
Assistant Editors: Yee Van Fan, Xue Xiu. Jia, Xue Chao Wang

Monitoring industrial steam cycle performance

V. Madron*, M. Hošťálek, L. Štěpán

ChemPlant Technology, s.r.o., Vinařská 1015/4, 400 01 Ústí nad Labem, Czech republic
vit.madron@chemplant.cz

Monitoring and Performance Analysis Systems (MPAS) can help maintain near optimum industrial production. But, the data available in process industries are frequently incomplete and data are sometimes corrupted by measurement or other errors. A major problem in designing a reliable industrial MPAS system is the availability and accuracy of needed measurements. The end result is that often on-line estimation of important process parameters and Key Performance Indicators (KPI) become complex tasks with uncertain results.
This work illustrates these problems, and provides possible solution, using a case study monitoring the performance of an industrial steam condenser. The steam condenser is a part of a cogeneration system providing electricity and steam for a petrochemical complex. A detailed model of the steam cycle, including the steam condenser, is presented. KPIs for the steam cycle overall efficiency include the condenser heat transfer coefficient and heat load and the quality of steam leaving the low-pressure turbine. Bottlenecks in accurately determining these KPIs are identified and ways to overcome limitations are discussed. Data driven modelling of the steam cycle targeted at process optimization is also described.

1. Introduction

Data measured in process industries (chemicals, oil & gas, power generation) are frequently incomplete and can be corrupted by measurement or other errors. Data validation is used to reduce the influence of random measurement errors and remove possible gross errors (Madron, 1992). Data validation also enhances data sets by allowing calculation of unmeasured process variables and model parameters (efficiencies, heat transfer coefficients, etc.). Data validation is based on data reconciliation which is now a standard technology for the monitoring, control and optimization of industrial processes.
However, a major problem in designing an industrial Monitoring and Performance Analysis Systems (MPAS) remains the availability and accuracy of the incoming data. Consequently the accuracy of the end result – the on-line estimation of important process parameters and Key Performance Indicators - is a complex task with uncertain results. An understanding of this uncertainty is essential. An analysis of this problem needs a detailed mathematical model based on the system mass, energy and momentum balances and thermodynamic relations (the physical model). In practice such model can be complemented by empirical relations based on statistical processing of historical process data. Such combined model also provides information needed for optimal selection of measuring points, optimization of measurement precision, parametric sensitivity, etc.

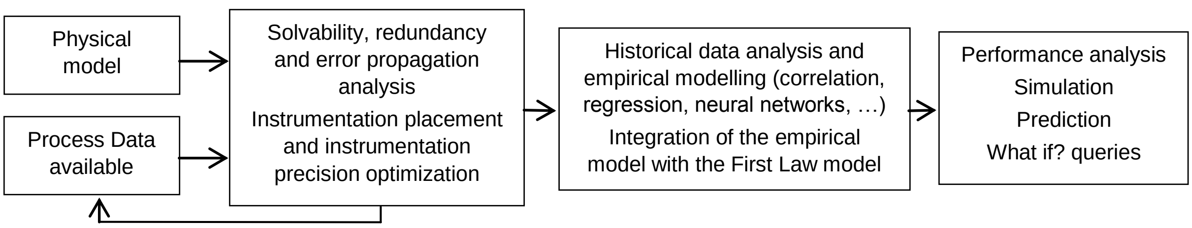

Fig. 1: Scheme of a Monitoring and Performance Analysis Systems

This approach depicted in Fig. 1 consists of (1) Creating a classical physical model (mass and energy balances, etc.), (2) Collecting information about available instrumentation including precision and accuracy, (3)

Analysis of solvability and redundancy. Analysis of errors propagation during data processing. Identifying bottlenecks of result's precision and improvement of input data quality. (4) Processing of historical data to complement the physical model by empirical findings (so-called *process data driven modelling*). (5) Such model can be used with confidence for plant performance analysis and operation improvement.
This work illustrates the problems with data collection and process performance monitoring using a case study of an industrial steam condenser. The steam condenser is part of a cogenerating system providing electricity and steam in a petrochemical complex. In addition to performance monitoring and diagnostics, data driven performance optimization is described.

2. The Steam Cycle

The condenser studied here (see Figure 2) is a part of an industrial steam cycle (SC) which consists of 3 turbines (High, Intermediate and Low pressure), a condenser, 2 low pressure heaters, 2 high pressure heaters, a deaerator, pumps and boiler (not analysed in this presentation). The surface condenser is cooled by cooling water. For details see Madron (2015)

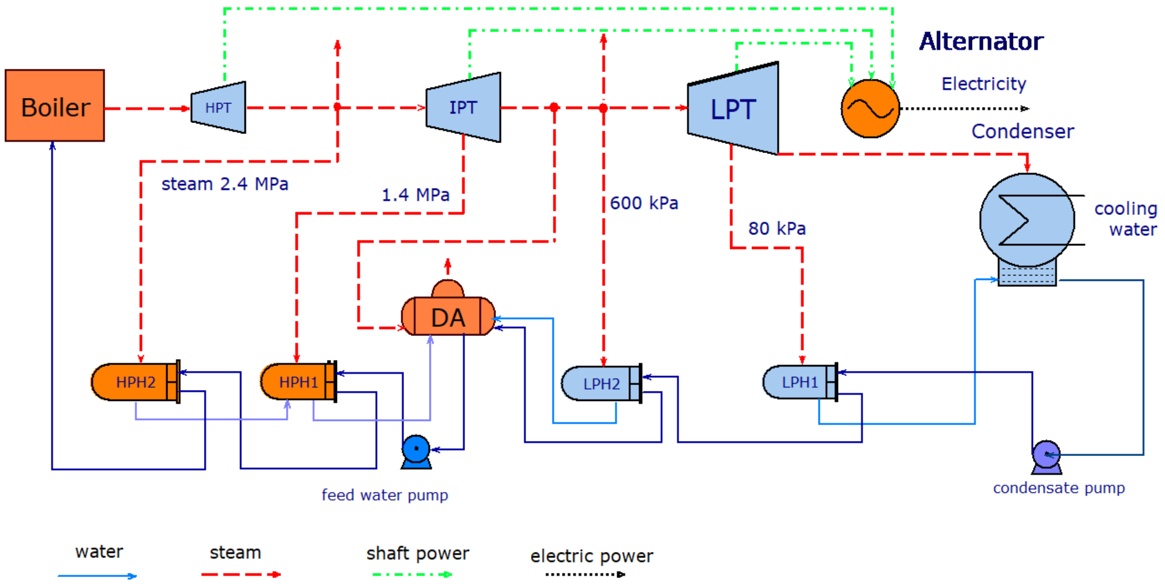

Fig.2: Steam cycle. HPH - High Pressure Heater, HPT - High Pressure Turbine, IPT - Intermediate Pressure Turbine, LPT - Low Pressure Turbine, LPH - Low Pressure Heater, DA - deaerator

3. Mathematical model

The mathematical model of the SC consists of:
- Mass and energy balances (enthalpy, kinetic and potential energy)
- momentum balances (modelling flow in pipes where pressure drop is significant)
- thermodynamic models (isentropic efficiency in steam turbines, heat transfer in heat exchangers)

The mathematical model can be formally written as a system of implicit nonlinear algebraic equations.

$$\underline{F}\left(\underline{x},\underline{y},\underline{c}\right)=\underline{0} \qquad (1)$$

where $\underline{F}(\ )$ is a vector of model equations
$\underline{x}$ is a vector of directly measured variables
$\underline{y}$ is a vector of unmeasured variables
$\underline{c}$ is a vector of precisely known constants

A model of the SC was created in the mass and energy balancing system RECON (RECON 2018), see also Madron (2015). Details of the modelling can be found in: Veverka and Madron (1997), for mass and energy balances; Gay, Palmer and Erbes (2006), for general power plant performance analysis; Cotton (1998), for steam turbines; and Putman (2001), for steam condensers and heaters. Properties of water and steam were calculated using IAPWS IF-97 (IAPWS 1998). The model of the SC in Fig. 2 consists of 65 equations, 25 measured and 62 unmeasured variables. The model can be switched between Step (1) reconciliation of the measured data and Step (2) prediction of plant behaviour based on the parameters determined in Step (1).

4. Process data reconciliation

The SC studied is equipped with more instrumentation/data than necessary for solving the model. The system of equations given by Eq (1) is therefore redundant and data reconciliation (DR) is essential. DR details are provided for example in Romagnoli and Sanchez (2001), Madron (1992) or Veverka.(2001).
With measured values $\underline{x}^+$ the system of Eq (1)

$$\underline{F}\left(\underline{x}^+,\underline{y},\underline{c}\right)\neq\underline{0} \qquad (2)$$

is generally not solvable, regardless of the values of the unmeasured variables. The basic idea of DR is to adjust the measured values in such a manner that the reconciled values are as close as possible to the true (but unknown) values. The reconciled values x_i' (marked by apostrophe) result from the relation

$$x_i'=x_i^+ + v_i \qquad (3)$$

where to the measured values, x_i^+ , so-called "adjustments" v_i , are added. In the ideal case, these adjustments would simply be equal to the unknown errors for each measurement. Here we utilize the mathematical model (mass balance, energy balance, etc.) that must be obeyed allowing the "correct values" to be determined as follows (method of "maximum likelihood"):
The adjustments must satisfy two fundamental conditions:

1) The reconciled values must satisfy Eq (1) – we say that they are consistent with the model

$$\underline{F}\left(\underline{x}',\underline{y}',\underline{c}\right)=\underline{0} \qquad (4)$$

2) The adjustments are minimal. Most frequently, the weighted sum of squares of the adjustments is minimized using the well-known Least Squares method

minimize

$$\sum\left(\frac{v_i}{\sigma_i}\right)^2=\sum\left[\frac{\left(x_i'-x_i^+\right)}{\sigma_i}\right]^2 \qquad (5)$$

Using the inverse values of variances σ_i^2 (squared standard deviations σ_i) – the so-called "measurement weights" – guarantee that more (statistically) precise values undergo less correction than the less precise ones (measurements with large variances are considered less precise); this is a relevant property of the method.
Schematically, this process can be imagined as the Data Reconciliation Engine depicted in Figure 3.

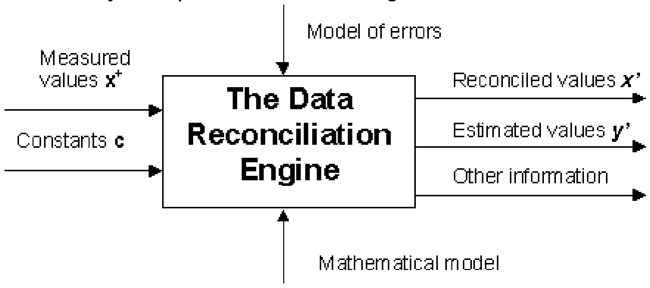

Fig. 3: The Data Reconciliation Engine

The "engine" thus transforms the input measured data (vector $\underline{x}^+$) to the reconciled $\underline{x}'$. In addition it computes/estimates the unmeasured variables $\underline{y}'$ and provides other information (mostly information about the uncertainties of the results) which will be needed in subsequent analysis.
We can then write for the unmeasured variables $\underline{y}'$ symbolically

$$\underline{y}'=\underline{h}\left(\underline{x}^+\right) \qquad (6)$$

These symbolic functions will be used later for calculations of parametric sensitivity and measurement error propagation.

5. Propagation of errors

The vector function (6) is the basis for analysis and optimization in a Monitoring and Performance Analysis System (MPAS). Linearization can be used to obtain the parametric sensitivity coefficients h_{ij},

$$h_{ij}=\frac{\partial h_i(x^+)}{\partial x_j} \tag{7}$$

representing the sensitivity of the unmeasured variables and model parameters on the directly measured variables. The original function (6) can be linearized in vicinity of the measured values (base-case value $y_{i(B)}$):

$$y_i = y_{i(B)} + h_{i1}\Delta x_1 + h_{i2}\Delta x_2 + \ldots + h_{ij}\Delta x_j + \ldots + h_{iJ}\Delta x_J \tag{8}$$

Here then the calculated variables y_i are linear functions of the measured variables x_j and the well-known Law of Errors' Propagation can be applied (Himmelblau 1970). Standard deviations of measurement errors σ_i represent measured values uncertainty. Other characteristics of measured values uncertainty are maximum measurement errors $e_{i,max}$ which are, in technical practice, taken as 1.96 multiples of σ_i. For variances, σ_{yi}^2 , and statistically independent measurement errors we can write,

$$\sigma_{yi}^2 = h_{i1}^2\,\sigma_{x1}^2 + h_{i2}\,\sigma_{x2}^2 + \ldots + h_{ij}^2\sigma_{xj}^2 + \ldots + h_{iJ}^2\sigma_{xJ}^2 \tag{9}$$

By multiplying Eq (9) by $1/\sigma_{yi}^2$ we get a more convenient equation

$$1 = \frac{h_{i1}^2\,\sigma_{x1}^2}{\sigma_{yi}^2} + \frac{h_{i2}\,\sigma_{x2}^2}{\sigma_{yi}^2} + \ldots + \frac{h_{ij}^2\,\sigma_{xj}^2}{\sigma_{yi}^2} + \ldots + \frac{h_{iJ}^2\,\sigma_{xJ}^2}{\sigma_{yi}^2} \tag{10}$$

where $h_{ij}^2\sigma_{xj}^2/\sigma_{yi}^2$ multiplied by 100 is the so-called *share* of *j-th* measured variable on the variance of *i-th* calculated variable y_i (Madron 1992). The individual items in Eq (10) are non-negative and each term on the right hand side of Eq (10) represents the % share of individual measured variable on the uncertainty of the results. It is clear that measured variables with "high share values" are the precision bottlenecks of the calculated results.

6. Case study - Monitoring and performance analysis of a condenser

The most important process indicators for the condenser are:

- heat load
- condensing steam pressure and quality
- cooling water flowrate and temperature.

The Key Performance Indicator of the condenser is its heat transfer coefficient (HTC) which must be included in the SC model. HTC is defined by Eq (11)

$$Q = HTC * A * LMTD \tag{11}$$

where Q = condenser heat load [W], HTC [$Wm^{-2}K^{-1}$], A = heat transfer Area [m^2], *LMTD* = Logarithmic Mean Temperature Difference [K].

When modelling the SC it is important to understand that the HTC is not a constant. It is significantly influenced by the cooling water flowrate and cooling water temperature and also (possibly) by fouling on the cooling water side of the heat exchange.

In the next we present results of the detailed analysis of important variables influencing the condenser's HTC estimation. But first, it is important to discuss the role/importance of Steam Quality (SQ).

SQ is defined as % of steam in the wet steam (the quality of saturated steam is 100 %). SQ is important for monitoring the isentropic efficiency of the low-pressure turbine and it is also essential when setting up the condenser's energy balance. Direct measurement of steam quality in industrial conditions is not easy. Cotton (1988) discusses several methods, but none are suitable for on-line industrial use. The only feasible way to determine steam quality is to calculate it from a mass and energy balance. This is the reason why an analysis of condenser's performance is not possible without a complete balance model of the entire steam cycle (the boiler is not needed in this balance).

For the condenser, two variants were considered/studied: (A) the flowrate of cooling water (CW) is measured, and (B) flowrate of cooling water is not measured (due to large pipe diameters it is sometimes difficult to measure it in practice).

The following uncertainties ± of directly measured variables were used: flowrates ± 2 %, temperatures < 100 ^{o}C ± 1 K, temperatures in the interval <100 to 300> ^{o}C ± 2 K, temperatures > 300 ^{o}C ± 3 K, pressure 1 %, and electricity generated 0.5 %.
Table1 shows examples of calculated condenser parameters and the resulting uncertainties.

Table 1: Calculated condenser parameters (variant A – CW flow is measured, Variant B – CW is unmeasured)

		Variant A			Variant B		
Variable	Unit	value	± (abs)	± (%)	value	± (abs)	± (%)
Condenser heat load	MW	79.7	1.5	1.9	79.7	1.5	1.9
Steam quality	%	94.5	0.8	0.8	94.4	0.8	0.8
HTC	$Wm^{-2}K^{-1}$	1,521	124	8.1	1,530	131	8.6

It can be seen that Variants A and B do not differ too much (values and their uncertainties). This means that measuring the CW flowrate is not an absolute necessity for determination of HTC. This can be understood by considering the overall balance on the SC which is based on measured flows of feed water, steam and generated electricity.
Let's now try to improve the uncertainty of HTC which is determined as over 8 % of its value in Table 1. Table 2 provides the "vector share values" of the most important measured variables (with shares > 1 %).

Table 2: Shares of measured variables on HTC variance

Measured variable	Unit	Variant A Share [%]	Variant B Share [%]
condenser pressure	kPa	5	5
cooling water input temperature	^{o}C	38	15
cooling water output temperature	^{o}C	48	75
feed water flowrate	t/h	2	1<
admission steam flowrate	t/h	2	1<
turbine condensate flowrate	t/h	2	1<

It is clear that HTC uncertainty can be significantly improved by lowering the uncertainty of the cooling water temperature, especially its output temperature. If the uncertainty of the output CW temperature is reduced to 0.5 K, the resulting HTC uncertainty is decreased to 83 $Wm^{-2}K^{-1}$ (5.4 %) for Variant A and to 87 $Wm^{-2}K^{-1}$ (5.7 %) for Variant B. It should be noted that these observations are valid only for the present configuration of the model the current measurement uncertainties) and should be recalculated after every change.

7. Process data driven modelling

Important process parameters, like the Heat Transfer Coefficients in the SC, are not constant but are functions of other process variables. While literature concerning modelling these parameters is numerous, it frequently provides results which are not in tune with reality. The natural method for modelling the HTC is a correlation and regression analysis (Himmelblau 1970) of historical process data. We have found that over 95 % of the HTC variability (coefficient of determination R^2) can be explained by cooling water temperature and flowrate, if fouling is eliminated by cooling water conditioning. It should be noted here that the cooling water flowrate is strongly correlated with the condenser heat load. It is therefore sometimes possible to replace in a regression model, the CW flowrate by the condenser heat load as an independent input variable. Figure 4 illustrates the use of statistical regression in modelling of a steam condenser based on historical process data. Fig. 4a) shows HTC calculated on the basis of linear empirical function of input cooling water temperature and flowrate versus HTC measured values. The next Fig. 4b) shows prediction of HTC calculated by the same way in time. Such simple empirical model can be easily integrated with the original physical model.
Empirical models, if they are regularly updated in time, can be efficiently used in an on-line performance analysis of existing industrial systems. This hybrid approach to modelling, which combines rigorous first law models with data driven empirical regression models, provides also a very reliable basis for decision support systems, answering What if? queries and also for process optimization.

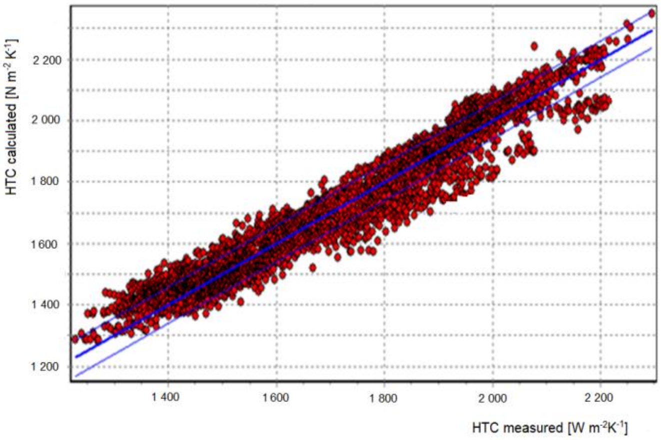

Fig 4: Correlation and regression analysis of HTC as a linear function of cooling water temperature and flowrate: Measured versus calculated HTC values

8. Conclusions

Process industries have the need for reliable mathematical models of high accuracy. Potential improvements in well-established industry sectors (bulk chemicals, oil & gas or power generation) are in order of few % at most, and frequently in the range of tenths of % only. Monitoring and Performance Analysis Systems, which utilize these mathematical models, allow near optimal process operation to be maintained. MPAS can be used to guide non-optimal processes to near optimal operation. The approach described in this presentation consists of:

1. Creation of mathematical models based on laws of nature.
2. Use of these models and available process data. Here data validation and data reconciliation should be used. Analysis of errors propagation during this process is essential.
3. The preceding step provides information about data measurement and data optimization (the need for improvement of individual measurements' precision; better instrumentation placement, etc.).
4. Long term monitoring provides an invaluable archive of validated historical data which can be used for creating empirical models (correlation and regression analysis, neural networks, etc.). Such information can enhance the quality of classical "first law" models as model parameters taken from standard handbooks or technical papers are frequently tens of per cent far from real values found in practice.
5. We recommend MPAS which utilizes a combination of first law models and empirical models based on process data. Such an MPAS approach can be used for decision support, studying What if? scenarios, process behaviour prediction and even for direct process optimization.

References

Cotton K.C, 1988, Evaluating and Improving Steam Turbine Performance, Cotton Fact Inc., Rexford, N.Y.

Gay R.R., Palmer C.A., Erbes M.R., 2006, Power Plant Performance Monitoring, Tech Books International, New Delhi, India

Himmelblau D.M., 1970, Process Analysis by Statistical Methods, John Wiley & Sons, New York

IAPWS Industrial Formulation 1997 for the Thermodynamic Properties of Water and Steam, International Association for the Properties of Water and Steam, 1998, ASME PRESS

Madron F, 1992, Process Plant Performance. Measurement and data processing for optimization and retrofits, Ellis Horwood, New York

Madron V., 2015, Steam Turbine Condenser (in Czech), BC Thesis, UJEP Usti nad Labem, Czech Republic

Putman R. E., 2001, Steam Surface Condensers: Basic Principles, Performance Monitoring, and Maintenance, ASME Press, New York

RECON® - Mass, Energy and Momentum balancing software with data reconciliation. <www.chemplant.cz/download.asp> accessed 28.02.2018

Romagnoli J.A., Sanchez M.C., Data Processing and Reconciliation for Chemical Process Operations, Academic Press, San Diego 2000, California

Veverka V.V., Madron F., 1997, Material and Energy Balancing in the Process industries. Elsevier, Amsterdam, The Netherlands

Veverka V.V., 2001, Balancing and Data Reconciliation Minibook, <www.chemplant.cz/download.asp> accessed 28.02.2018